OPTOELECTRONIC NEURAL NETWORKS. OPTICAL INTERCONNECTION OF NEURONS BY COMPUTER GENERATED HOLOGRAMS (II)

by
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Abstract: This article is the second part of a work dealing with the optoelectronic implementation of artificial neural networks. The authors analyze the problems involved by using computer-generated holograms (CGH) for these interconnections and some methods of designing such diffractive elements. The authors also analyze the error sources and the consequences caused by random deviations of the neurons interconnection weights from the accurately computed values. The theoretical considerations are illustrated by designing an auto associative memory built for graphic pattern recognition. Neurons interconnections are to be implemented optically by computer generated holograms (CGH). The network functioning was simulated on computer and the paper presents also the results of simulations on a data set and a CGH layout for neuron interconnections.

Keywords: Optical interconnections, computer generated holograms, weights matrix, random deviations.

1. ERROR SOURCES FOR OPTICAL INTERCONNECTION WITH CGH. INFLUENCE OF RANDOM WEIGHT DEVIATIONS

Implementing optical interconnection with CGH implies the following steps: synthesis of CGH for the synaptic weights matrix W; building and aligning the optical setup. In the following we will briefly review the errors that may occur in the optical implementation of interconnections, leading to deviations of the real weight values from the accurate ones.

A. During the CGH computing step, the errors are due to the hologram synthesis method, as well as to the quantization of the obtained values [8] [9], [11]. When using Fourier amplitude holograms, a frequent difficulty is connected to the dynamic range of Fourier coefficients to be materialized in hologram. The computed range would lead to a smaller number of large aperture cells, most of the apertures being small, which significantly diminishes the hologram efficiency on diffraction. Consequently, dynamic range compression is required, with direct influence on the accuracy of the resulting synaptic weights.

During the CGH materialization step, the errors may occur from the unsatisfactory resolution of the devices involved or from the photolithographic process.

B. During the building of optical setup (the hardware implementation of the neural network), the following error sources may appear:

- Un-uniform optical emission of the photoemitters from the output plane of the neural layer (the input plane of the optical interconnection system)
- Un-uniform sensitivity of the photodetectors in the input plane of the neural layer (the output plane of the optical interconnection system)
- Axial misalignment (translation or rotation) of the three planes: the input plane, the hologram plane and the output plane.
- Errors concerning the positioning of individual photoemitters or photodetectors in their corresponding plane.
- Errors due to the variation of the geometrical dimensions of the setup, as a result of temperature variations.
- Errors caused by interaction of the adjacent optical paths (the light flow deviated by the hologram to a certain photodetector also reaches the nearby photodetectors).

All the errors above can be minimized, but it is obvious they cannot be completely removed. Consequently, we find very useful an analysis of the influences these errors might have on the global behaviour of the network.

In the following, we will present a general qualitative study on the effects of the weight deviations from the accurate values. The neural network had in sight for this analysis is an autoassociative neural network which stores p n-dimensional prototype vectors $>^{1}, >^{2},..., >^{p}$. We'll denote by **W** the accurate (theoretical) weight matrix and by $\mathbf{W}^*$ the real weight matrix. We may then consider:

$$\mathbf{W}^* = \mathbf{W} + \delta\mathbf{W} \tag{1}$$

where $*\mathbf{W}$ is a matrix of deviations from the computed values.

An energy function is defined for the neural network. The network's dynamics is associated to this energy function and one can easily see that the weight values deviations will have important consequences on the network's functioning. Thus, the random deviations of synaptic weights values can cancel the symmetry of **W** matrix and the property of diagonal elements (e. g. they may become negative), making the results concerning stability no longer valid. A non-symmetric or negative diagonal weight matrix may lead to the occurrence of cycles in the network's evolution. Therefore, the network won't reach a stable state; consequently it won't work well as associative memory.

The weight matrix synthesis starts from a set of prototype vectors we wish to be stored. From energy perspective, these prototypes are global minimum of function E (of value $-E_0$). If instead of the accurate **W** matrix the network operates using the $\mathbf{W}^*$ matrix, the energy value for some prototype becomes:

$$\mathbf{E}(\xi) = -\frac{1}{2}\xi^{\mathbf{T}}\mathbf{W}\xi - \frac{1}{2}\xi^{\mathbf{T}}\delta\mathbf{W}\xi = \mathbf{E}_0 + \delta\mathbf{E} \tag{2}$$

One may observe that the weights deviation from accurate values will **modify the "energy landscape"**. The prototypes minimum may change, as well as spurious states minimums may occur.

Up to this point we didn't make any assumption on the range or statistical distribution of deviations. A more detailed analysis is performed in [4], to see the influence of deviations on the maximum number of prototypes the memory can store. The main result of this analysis is that, if the weight deviations obey a gaussian distribution with the variance Φ_*^2, then, in case of Heb's rule, the maximum number of patterns that can be stored is:

$$\mathbf{p} \le (0.138 - \sigma_\delta^2) \cdot \mathbf{n} \qquad (3)$$

One can thus see that random deviations of the weights can seriously **affect the maximum number of prototypes** that may be stored in the network, as well.

2. EXPERIMENTAL RESULTS

We performed a series of simulations in order to investigate the following problems concerning the interconnection of artificial neurons by CGH: the influence on the behaviour of the network of the random deviations of weights due to tehnological errors, the design of interconnection CGH. In this simulations we considered the recurrent neural network in figure 1, designed as autoassociative memory. In that concern the interconnection by CGH, we considered the solution proposed by A. Keller in references [6], [7] using, for each neuron, one holograms to connect it to the other n neurons.

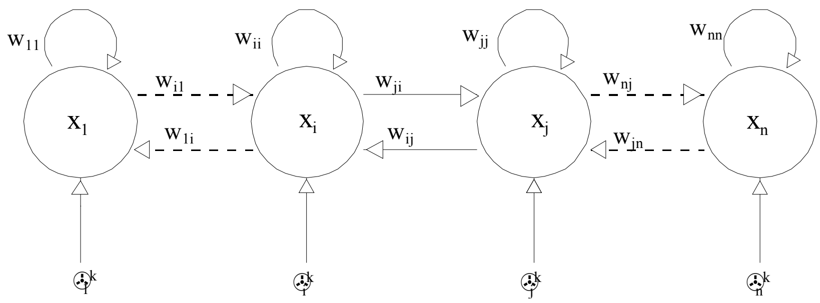

Fig. 1. Single layer recurrent neural network

2.1. The influence of random deviations of the weights

The errors shown in previous section can produce, as we said, deviations of the real interconnection weights from the exact values. In order to see the influence of these deviations we've performed a large number of simulations in order to verify the theoretical considerations from the precedent section. We've studied an autoassociative neural network, synthesized starting from a set of 10 prototypes representing the cursive script numerals 0..9. The simulations have had in view the influence that random weight deviations have on the following network features:

- Noise tolerance. The network had to recognize noise affected prototypes, using the accurate **W** matrix, and also the deviated weights matrix $\mathbf{W}^*$**.**
- The energy minimums corresponding to prototypes. For the 10 prototypes we have computed the energy minimums, in the accurate weights phase, as well as using the deviated weights.
- The average number of iterations before stabilizing into an attractor.

The results we've obtained are illustrated below:

I. When the associative memory operates with the accurate weights, it shows a very good noise immunity, recognizing prototypes affected by up to 40% noise. If the weight matrix used is $\mathbf{W}^*$, the noise immunity decreases, so that the network is no longer able to recognize prototypes with the same noise contamination.

II. In order to study the above-mentioned objectives, we've performed several simulations affecting the weight matrix **W** with random deviations having various distribution laws and parameters. A set of simulations pursued the altering of the accurate matrix with random deviations having a gaussian distribution, with different mean and variance values. For each case, we've performed 100 recognitions of every prototype, disturbed by 40% noise. The results are shown in fig. 2.

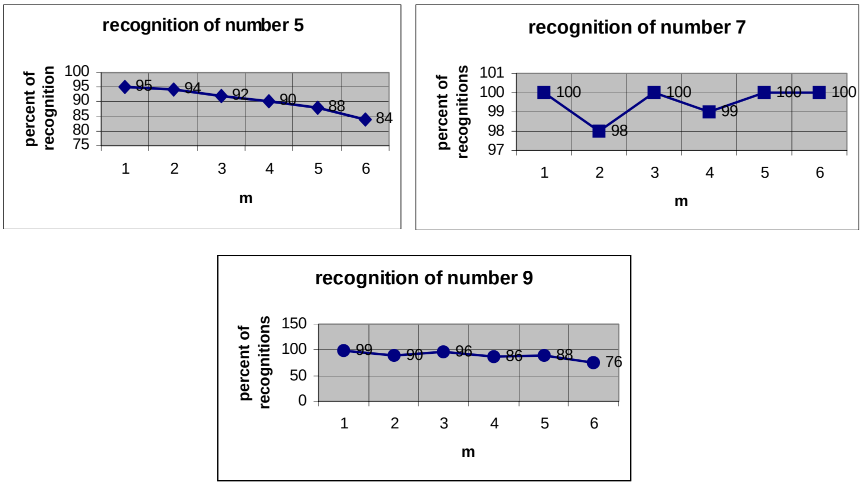

Fig. 2. Recognition of some noisy prototypes by the network with weights disturbed by gaussian deviations with variance $\Phi_*^2 - m^2 \Phi_w^2$

III. For every deviated matrix we used, we've computed the prototype corresponding energy values, watching the energy minimum's variations. The simulations outlined, for the above cases, a slight disturbance of the energy minimums (about 3% of the values corresponding to the accurate weights). Also, we've noticed that the average number of iterations slightly varies from the value of 3, no matter which the weights deviations are.

2.2. Example of CGH design

An other attempt of our crew was to design an example of interconnection CGH. We considered a more simple recurrent network, designed to recognise the graphical patterns in figure 3. The network was organized as a plan of 16x16 neurons. In our approach it is neccessary a CGH for every neuron, to achieve the interconnection of this neuron to all other neurons in network. We calculated only one interconnection CGH, from neuron (1,1) to the other neurons in network. The method used was "detour phase", with no error correction. Because the amplitude dynamic range resulted after Fourier transform was too great, we compressed this dynamic range. The resulting layout is displayd in figure 4.

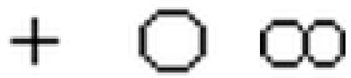

Fig. 3. Graphical patterns used as prototypes

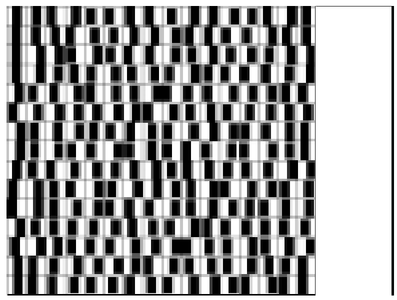

Fig. 4. Layout of CGH connecting neuron (1,1) to the other neurons

3. CONCLUSIONS

The interconnections of optoelectronic neuron by means of CGH seem to be a useful solution to satisfy the necessity of dense connectivity. There are, nevertheless, several problems due to the spatial variant interconnection and to diffraction efficiency. Other problems appear as consequences of errors which can appear in the realization of CGH and in optical setup. The simulations have shown diminished performances of the autoassociative memory as a result of the random weights deviations from the correctly computed values. For the statistical parameters used above the performances' degradation is relatively small, which proves certain insensitivity to those deviations. Therefore, the memory appears quite robust, not only in what the noise contained by the patterns to be recognized is concerned, but also in relation with the random weights deviations.

This aspect is to be elucidated in further studies. It would also be useful to determine quantitatively the contribution of the errors described in section 4 to the deviation of actual weights from accurate ones, in order to state realistic requests for the hardware implementation of the autoassociative memory.

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